Comparison of Advanced Pixel Based (ANN and SVM) and Object-Oriented Classification Approaches Using Landsat-7 Etm+ Data

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In this study, the pixel-based and object-oriented image classification approaches were used for identifying different land use types in Karnal district. Imagery from Landsat-7 ETM with 6 spectral bands was used to perform the image classification. Ground truth data were collected from the available maps, personal knowledge and communication with the local people. In order to prepare land use map different approaches: Artificial Neural Network (ANN) and Support Vector Machine (SVM) were used. For performing object oriented classification eCognition software was used. During the object oriented classification, in first step several different sets of parameters were used for image segmentation and in second step nearest neighbor classifier was used for classification. Outcome from the classification works show that the object-oriented approach gave more accurate results (including higher producer's and user's accuracy for most of the land cover classes) than those achieved by pixel-based classification algorithms. It is also observed that ANN performed better as compared to SVM classification approach.

KEY WORDS: Land Cover, Classification, Landsat, Multispectral, ANN, SVM, object oriented.

1. Introduction

Image classification is an important task for preparing Land use which is useful in many aspects of global change studies and environmental applications. The various approaches are available for image classification which includes conventional approaches such as maximum likelihood, minimum distance, parallelepiped, ISODATA, K-mean etc. and advanced techniques such as ANN, SVM[1]. The conventional approaches use only gray values on the other hand the advanced techniques such as ANN, SVM and object oriented classification considers the texture, tone etc. The use of textural features in ANN helps to resolve misclassification whereas SVM is capable of handling high dimensional datasets[2].

Object-oriented classification considers various parameters such as form, textures and spectral information. In object oriented classification first step is of grouping neighboring pixels into meaningful areas called as segments, which will be used in the later step of classification. Segmentation is based on the resolution of image and scale of expected objects. This segmentation can be done in multiple resolutions, thus allowing differentiating several levels of object categories.

In this study, Landsat-7 ETM image of Karnal District has been realized by EVNI 4.3 and eCognition 4.0 software packages. Pixel-based and the object-based classification techniques have been used for identification of different land use types. Successful segmentation was achieved by repeating the segmentation process with different set of parameters. The classification was performed based on the nearest neighbour analysis in the software.

2. Study Area and data used

2.1 Study Area

Karnal district lies on western bank of river Yamuna which flows through northern part of India. Karnal is located at 29.43^{o} N latitude and 76.58^{o} E longitudes and is about 250 meters above mean sea level[3]. The topography of Karnal district is almost plain and well irrigated through canals and tube-wells.

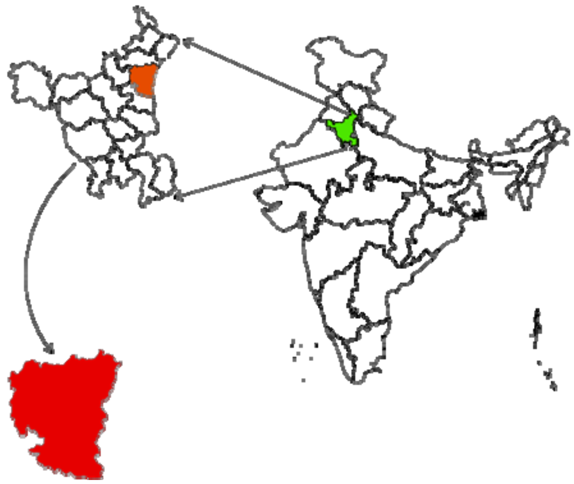


Figure 1: Study area

The climate of the district is dry and hot in summer and cold in winter. Its maximum and minimum temperatures vary from 43^{o}C to 21.5^{o}C in June and from 22^{o}C to 4^{o}C in January. The land of Karnal district is plain and productive. The soil texture varies from sandy loam to clay loam. The soils are alluvial and are ideal for crops like wheat, rice, sugarcane, vegetables etc.

2.2 Data used

For the present study area Landsat ETM+ image was used. The image was acquired on 10th February 2003.

Table 1. Landsat ETM+ Technical Specifications

Sensor type	opto-mechanical
Spatial Resolution	30 m (60 m - thermal, 15-m pan)
Spectral Range	0.45 - 12.5 µm
Number of Bands	8
Temporal Resolution	16 days
Image Size	183 km X 170 km
Swath	183 km
Programmable	yes

3. Materials and methods

3.1 Preprocessing of Landsat ETM+ data

Landsat ETM+ image was processed in order to prepare mask for the area. The processing includes conversion of DN values into radiance; the following formula was used for conversion[4]

$$L_{\lambda} = \left(\frac{LMAX - LMIN}{QCALMAX - QCALMIN} \right) X \left(DN - QCALMIN \right) + LMIN$$

where LMAX, LMIN, QCALMAX and QCALMIN were taken from header file of the image for each band. The equations prepared for calculating radiance values for each band are as follows,

R_1 = [1.18 * (DN-1)] – 6.2

R_2 = [1.204 * (DN-1)] - 6.4

R_3 = [0.945* (DN-1)] – 5

R_4 = [0.639* (DN-1)] – 5.1

R_5 = [0.126* (DN-1)] + 1

R_{61} = [0.067* (DN-1)]

R_{62} = [0.037* (DN-1)] + 3.2

R_7 = [0.044* (DN-1)] – 0.350

R_8 = [0.975* (DN-1)] – 4.7

where, R_{band} is the radiance image of a particular band and DN is the digital number of the input pixel. The Karnal district boundary map was overlaid on the radiance image to extract the study area. This radiance image is used as input for classifiers.

Figure 2. Radiance Image

3.2 Classifiers

The main purpose of classification is to automatically categorize all pixels in an image into classes or themes of land use types. This study emphasizes on the comparison between advanced pixel based (ANN, SVM) and object oriented classification techniques.

3.2.1 ANN

ANN is a parallel distributed processor that has a natural tendency for storing experimental knowledge. Image classification using neural networks is done by texture feature extraction and then applying the back propagation algorithm. The typical back-propagation network has an input layer, an output layer, and at least one hidden layer. There is no theoretical limit on the number of hidden layers but typically there are just one or two. Each layer is fully connected to the succeeding layer. The Neural Net technique in ENVI software uses standard back propagation for supervised learning. Learning occurs by adjusting the weights in the node to minimize the difference between the output node activation and the output.[5] The error is back propagated through the network and weight adjustment is made using a recursive method.

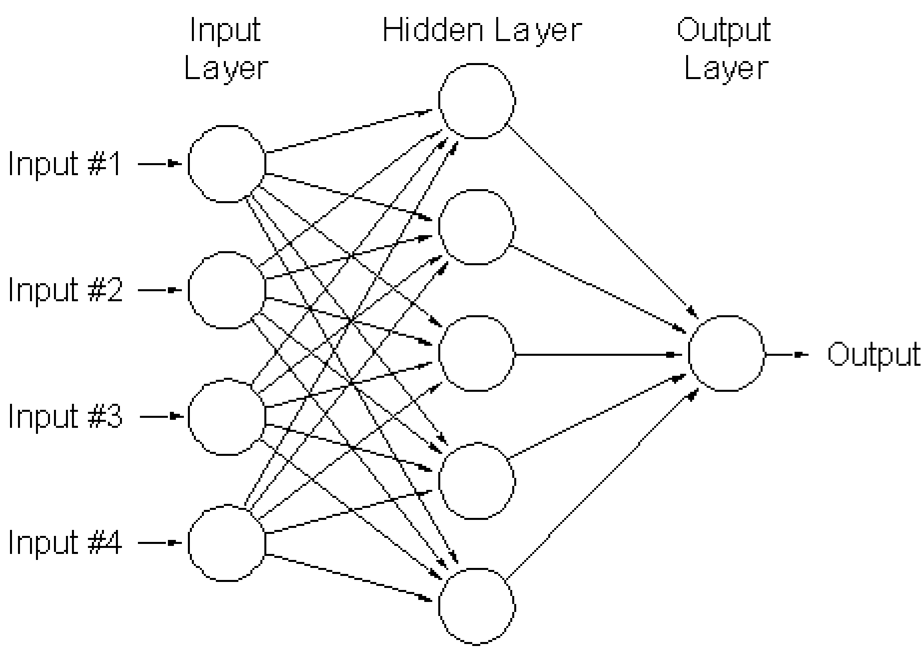


Figure 3. ANN architecture

3.2.2 SVM

SVM is a classification system derived from statistical learning theory. It separates the classes with a decision surface that maximizes the margin between the classes. The surface is often called the optimal hyper plane, and the data points closest to the hyper plane are called support vectors. The support vectors are the critical elements of the training set. ENVI's implementation of SVM uses the pair wise classification strategy for multiclass classification. SVM classification output is the decision values of each pixel for each class, which are used for probability estimates. ENVI performs classification by selecting the highest probability. An optional threshold allows reporting pixels with all probability values less than the threshold as unclassified. SVM includes a penalty parameter that allows a certain degree of misclassification, which is particularly important for non-separable training sets. The penalty parameter controls the trade-off between allowing training errors and forcing rigid margins[5].

3.2.3 Object oriented classification

Object oriented classification takes place inSegmentation is a process of partitioning of image into space into same non-overlapping meaningful homogenous regions. The term meaningful is problem dependent. The process of image segmentation involves subdivision or partitioning of image into homogeneous and disjoint regions of different statistical behavior called image segments. This regions consist of groupings of multispectral or hyperspectral image pixels that have similar data feature values. The image segments may be later associated with information levels, but segmentation process simply gives each region a generic level. In the context of earth remote sensing, these labels would generally be a ground cover type or land use category[6].

In the segmentation phase, following parameters should be assigned as accurate as possible, of course, suiting with the reality.

- Scale parameter: this parameter indirectly influences the average object size. In fact this parameter determines the maximal allowed heterogeneity of the objects. The larger the scale parameter the larger the objects become.
- Colour/Shape: with these parameters the influence of colour vs. shape homogeneity on the object generation can be adjusted. The higher the shape criterion the less spectral homogeneity influences the object generation.
- Smoothness/Compactness: when the shape criterion is larger than 0 the user can determine whether the objects shall become more compact (fringed) or more smooth.

Segmentation phase is followed by the classification of images. eCoginition software offers two basic classifiers: a nearest neighbor classifier and fuzzy membership functions. Both act as class descriptors. While the nearest neighbor classifier describes the classes to detect by sample objects for each class which the user has to determine, fuzzy membership functions describe intervals of feature characteristics wherein the objects do belong to a certain class or not by a certain degree. Thereby each feature offered by eCognition can be used either to describe fuzzy membership functions or to determine the feature space for the nearest neighbour classifier. A class then is described by combining one or more class descriptors by means of fuzzy-logic operators or by means of inheritance or a combination of both (see Figure 1). As the class hierarchy should reflect the image content with respect to scale the creation of level classes is very useful. These classes represent the generated levels derived from the image segmentation and are simply described by formulating their belonging to a certain level. Classes which only occur within these levels inherit this property from the level classes. This technique usually helps to clearly structure the class hierarchy

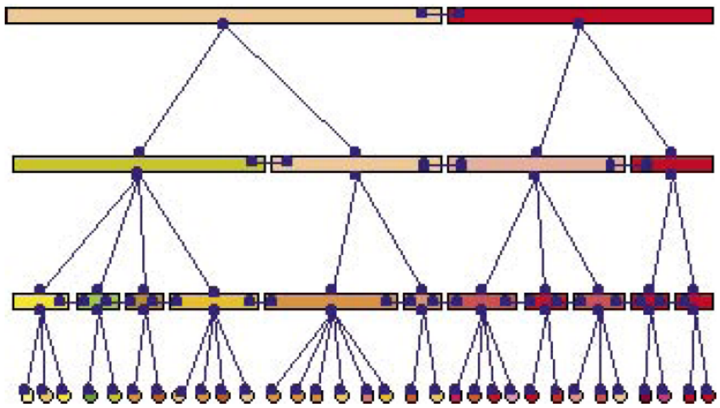


Figure 4. Hierarchical network of image

4. Classification and results

4.1 Advanced Pixel-based classification

In the first phase, Landsat image was subjected to ANN by providing training sites, which gives pre-knowledge about the study area. Classification has been in ENVI 4.3 software package and output of classification shown in Figure 5.

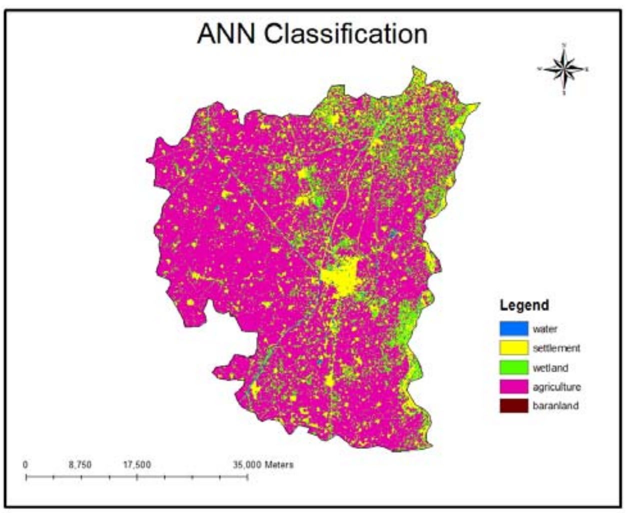


Figure 5. Result of ANN classification

In the second stage, SVM classification algorithm has been applied to the Landsat image based on the determined training patterns and reference materials. For comparative analysis of each method, same training sites have been utilized. Classification has been undertaken by the related module of ENVI 4.3 software package and respective image output is given in Figure 6.

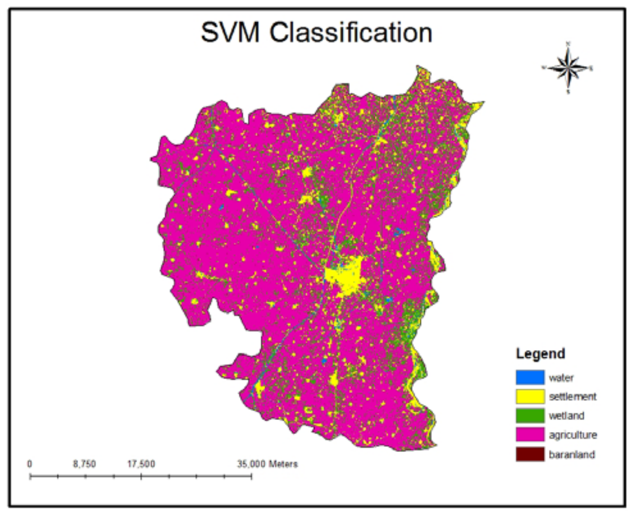


Figure 6. Result of SVM classification

4.2 Object-based Classification

Object-based segmentations were tried using different scale parameters given in Table 2. It can be realized that the smaller scale increases the dimensionality and dividing the object into the sub-groups, while the larger scale combines the multi-segments into one.

Table 2. Segmentation parameters used for Landsat ETM+

Level	Scale parameter	Colour	Shape	Smoothness	compactness
Level 1	5	0.7	0.3	0.9	0.1
Level 2	10	0.5	0.5	0.5	0.5
Level 3	20	1	0	0.5	0.5

From the acquired levels, most suitable one, level-3 has been selected for the classification of Landsat 7 image. Based on the properties of each spectral band, segments have been analyzed with different parameters in the related classes. As a result, the prominent segments are grouped and located in the corresponding classes. Then, classification procedure is completed by assigning the relevant class colour to segments and classified image is represented in Figure 7.

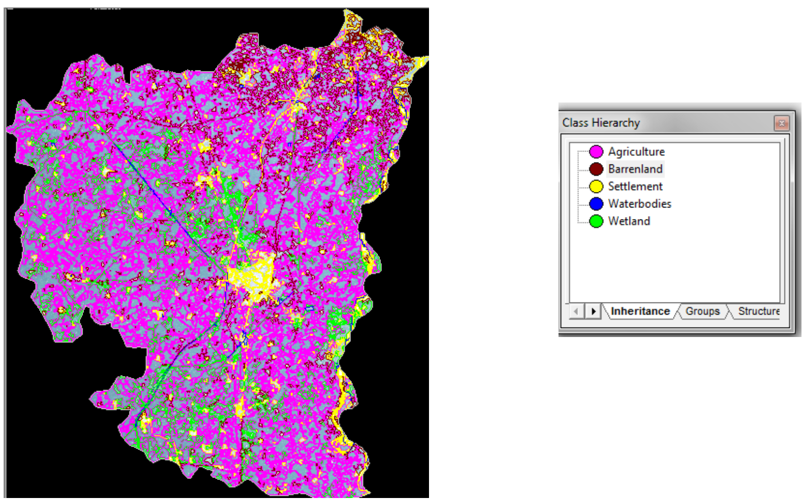
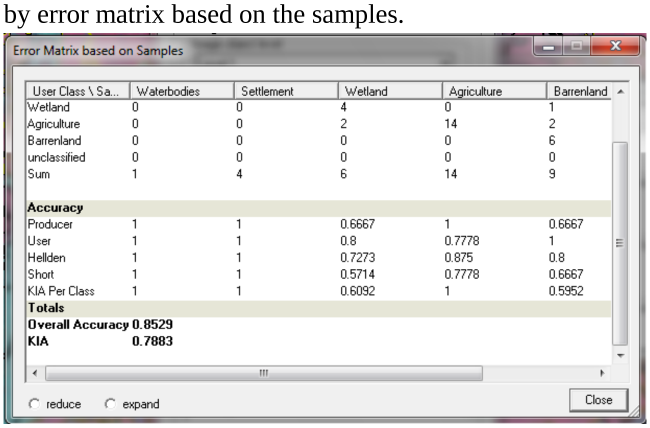


Figure 7. Results of Object-based classification

After classification phase, eCoginiton software gives the users ccuracy statistics of the acquired classes. Figure 8 shows such statistics of the classified image by error matrix based on the samples.



Error Matrix based on Samples

User Class \ Sa...	Waterbodies	Settlement	Wetland	Agriculture	Barrenland
Wetland	0	0	4	0	1
Agriculture	0	0	2	14	2
Barrenland	0	0	0	0	6
unclassified	0	0	0	0	0
Sum	1	4	6	14	9
Accuracy					
Producer	1	1	0.6667	1	0.6667
User	1	1	0.8	0.7778	1
Hellden	1	1	0.7273	0.875	0.8
Short	1	1	0.5714	0.7778	0.6667
KIA Per Class	1	1	0.6092	1	0.5952
Totals					
Overall Accuracy	**0.8529**				
KIA	**0.7883**				

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Figure 8. Error matrix and statistical values for Level 3.

4.3 Accuracy Assessment

Classification accuracy in remote sensing is to determine the agreement between the selected reference materials and the classified data. For this purpose, 730 pixels in the study have been selected randomly and their agreement with ground truth has been analyzed. Then, error matrix has been generated and given in Table 3. This table includes not only the producer's and the user's accuracy values but also the kappa statistics.

Table 3: producer's and the user's accuracy of advanced pixel based and object oriented classification

Class name	ANN			SVM			Object oriented classification		
	Producer accuracy	User accuracy	Kappa statistics	Producer accuracy	User accuracy	Kappa statistics	Producer accuracy	User accuracy	Kappa statistics
water	100	80	0.75	88.89	80	0.7419	100	100	1
settlement	75	90	0.8571	72.73	80	0.7241	100	100	1
wetland	80	80	0.7333	70	70	0.6	66.6	80	0.6092
agriculture	80	80	0.7333	70	70	0.6	100	77.8	1
barren land	0	0	0	0	0	0	66.7	100	0.5952

Looking at the Table 3, three out of five classes, namely water, settlement and agriculture, gave 100% producer accuracy and their kappa statistics were obtained as 1. The class, barren land, gave 100% user accuracy, but was however not detected by pixel based methods ANN and SVM. Wetland class gave much lower producer accuracy but had an equal or better percentage user accuracy, in case of object oriented classification. In general, amongst the pixel-based approaches, ANN gives the most accurate results. The reason behind is that in this method, that it uses the texture information to resolves misclassification. The object oriented approach, however, has proved to be superior in the present study.

Table 4 : Accuracy results from advanced pixel-based classifications and object-oriented image analysis

Accuracy statistics	ANN	SVM	Object oriented classification
Overall accuracy	82.5	75.00	85.29
Overall kappa statistics	0.7667	0.6667	0.7883

Object-oriented classification produced more accurate results as shown in Table 4. The reason for this is that the compactness of the segments. Thus, kappa and the overall accuracy are much better. In table 4, while overall accuracy was 85.29 for object-based segmentation, it was only 75.00 and 82.5 for the SVM and ANN classification methods respectively. For kappa values, some trends occurred and it is 0.7883 for object-based image analysis.

5. Conclusion

In this paper, object-oriented image classification technique has been compared with the advanced image classification methods using Landsat-7 ETM image of Karnal district, India. In the implementation of the tests, artificial neural network and support vector machine approaches are taken as pixel-based methods. Their capacity with used Lansdat image has been analysed based on the ground truth materials over the interest area. However, on the other hand, eCognition software for object-based classification works in hierarchy, first with segmentation, then the fuzzy classification. Detailed accuracy results were obtained as error matrices and they show that the object-based image analysis is far beyond the ANN and SVM in terms of accurate classification of the objects.

6. References

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